



# Learning an inverse model for vocal production: toward a bio-inspired model

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# Learning an inverse model for vocal production: toward a bio-inspired model

6th European Birdsong Meeting, April 12-13, 2018, Odense, Denmark

Silvia Pagliarini

(with Xavier Hinaut and Arthur Leblois)

*INRIA Bordeaux Sud-Ouest, Institut des Maladies Neurodégénératives, Université de Bordeaux, FR*

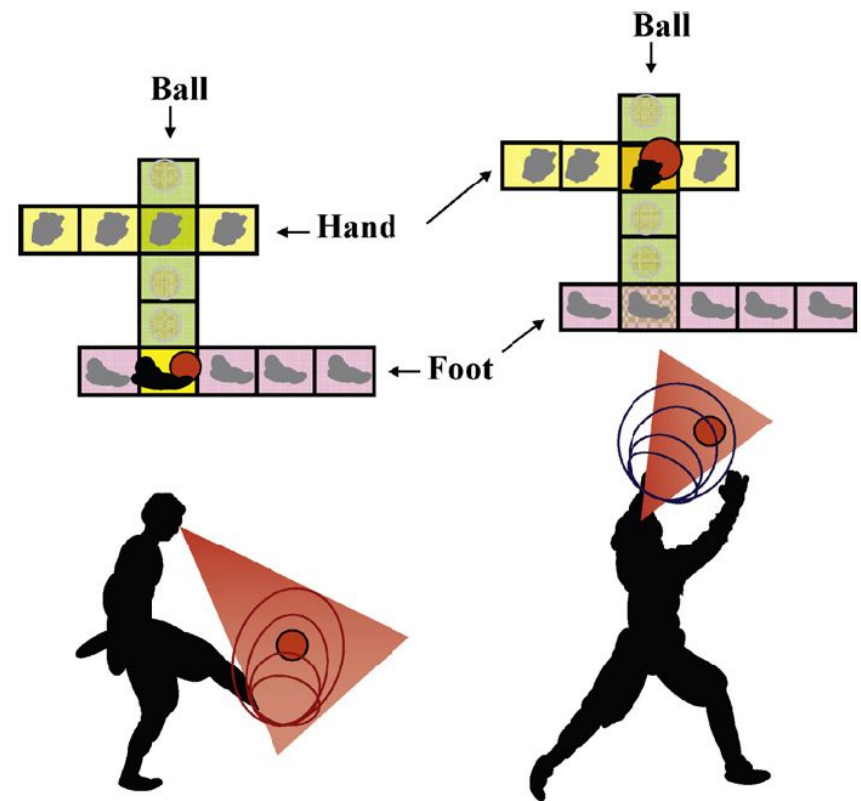


# WHAT IS SENSORIMOTOR LEARNING?

Control problem which maps a sensory input into a motor output

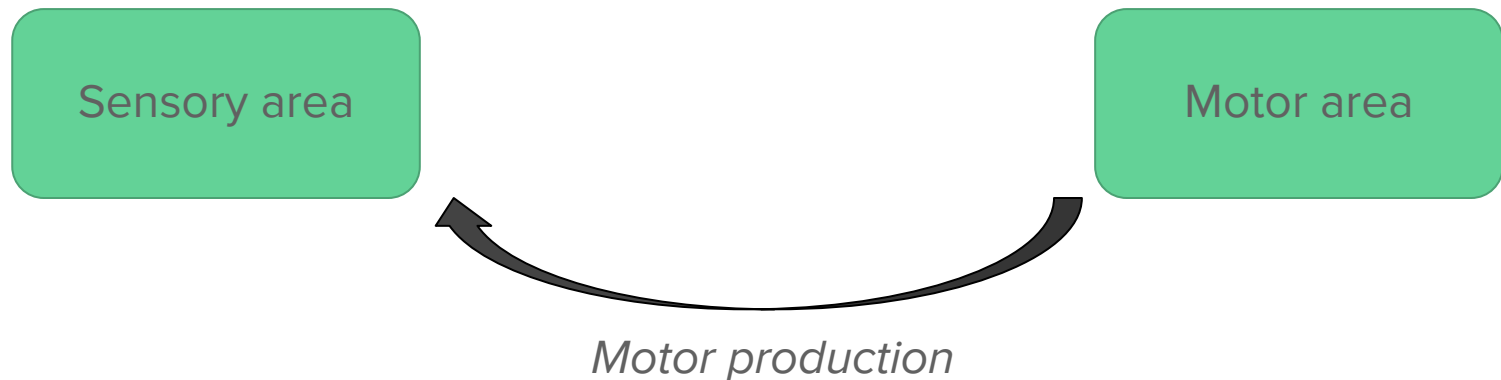
Basic components:

- Input: sensory stimulus
- Output: reproduction of the stimulus



# LEARNING BY IMITATION AND INVERSE MODEL

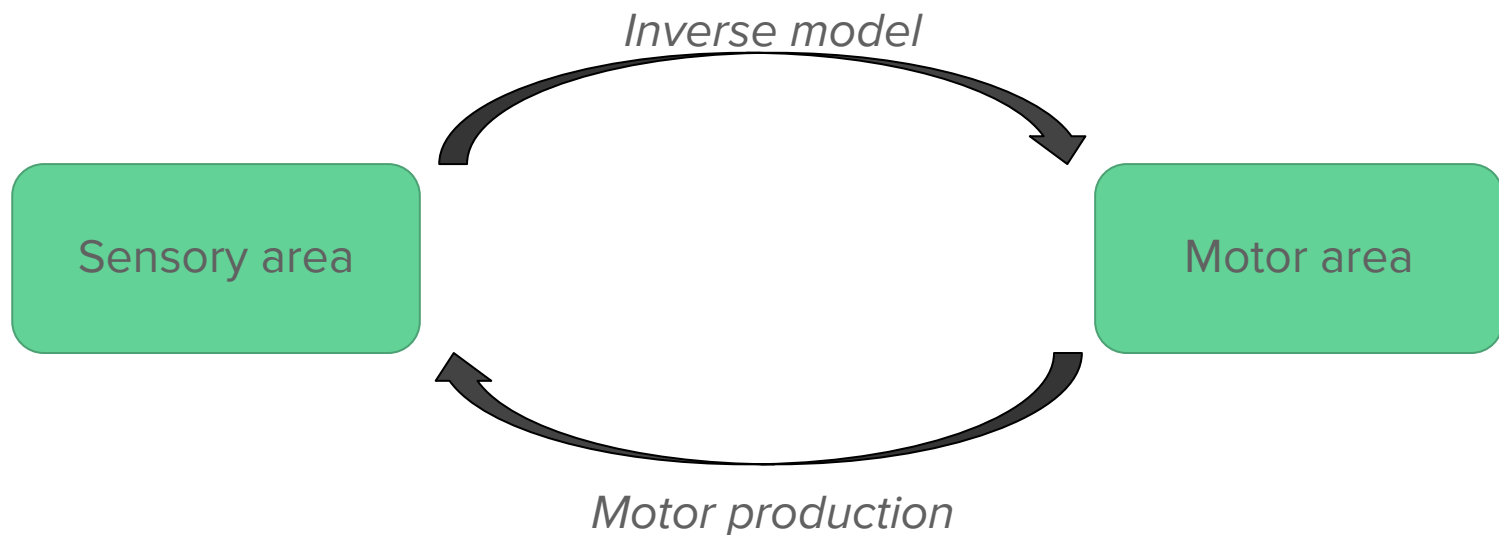
**Imitation:** learning from a tutor using a feedback guided error



# LEARNING BY IMITATION AND INVERSE MODEL

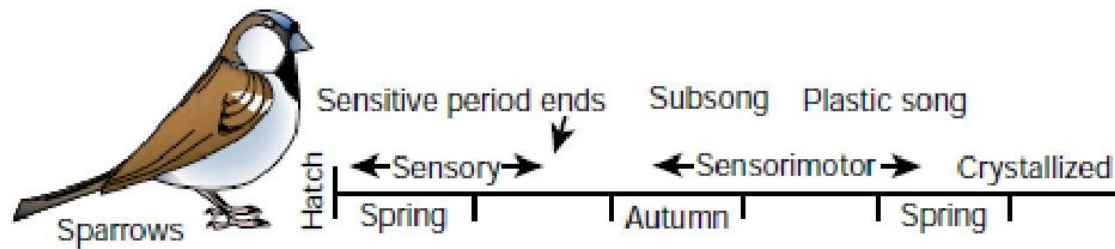
**Imitation:** learning from a tutor using a feedback guided error

**Inverse model:** the aim is to transform a sensory stimulus into the corresponding motor command



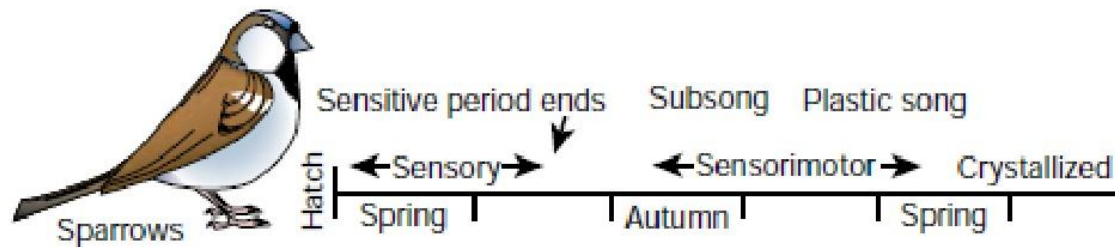
# A BIOLOGICAL EXAMPLE: SONG LEARNING IN BIRDS

- Comparable learning mechanisms and behavior



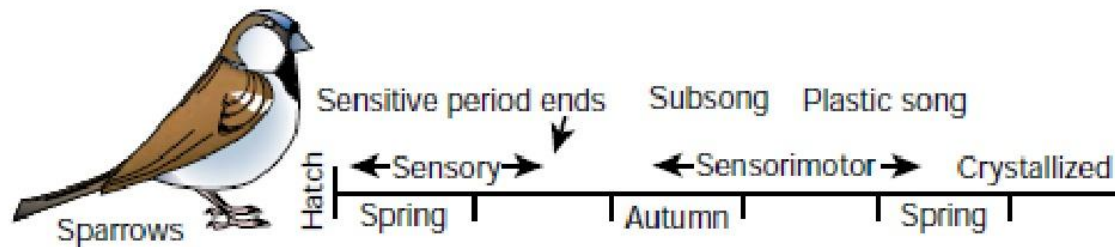
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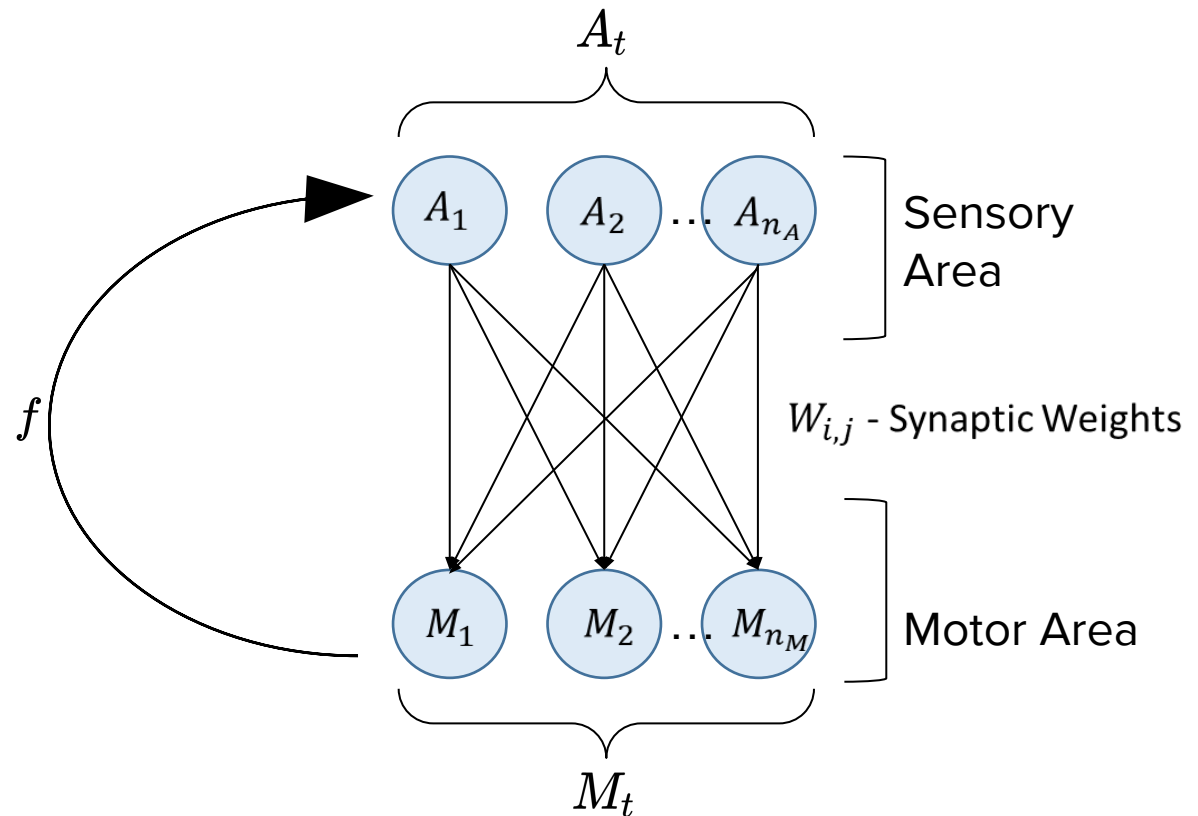
- Comparable learning mechanisms and behavior





# LEARNING AN INVERSE MODEL

Synaptic weights  $W_{t=t_0}$  initially weak

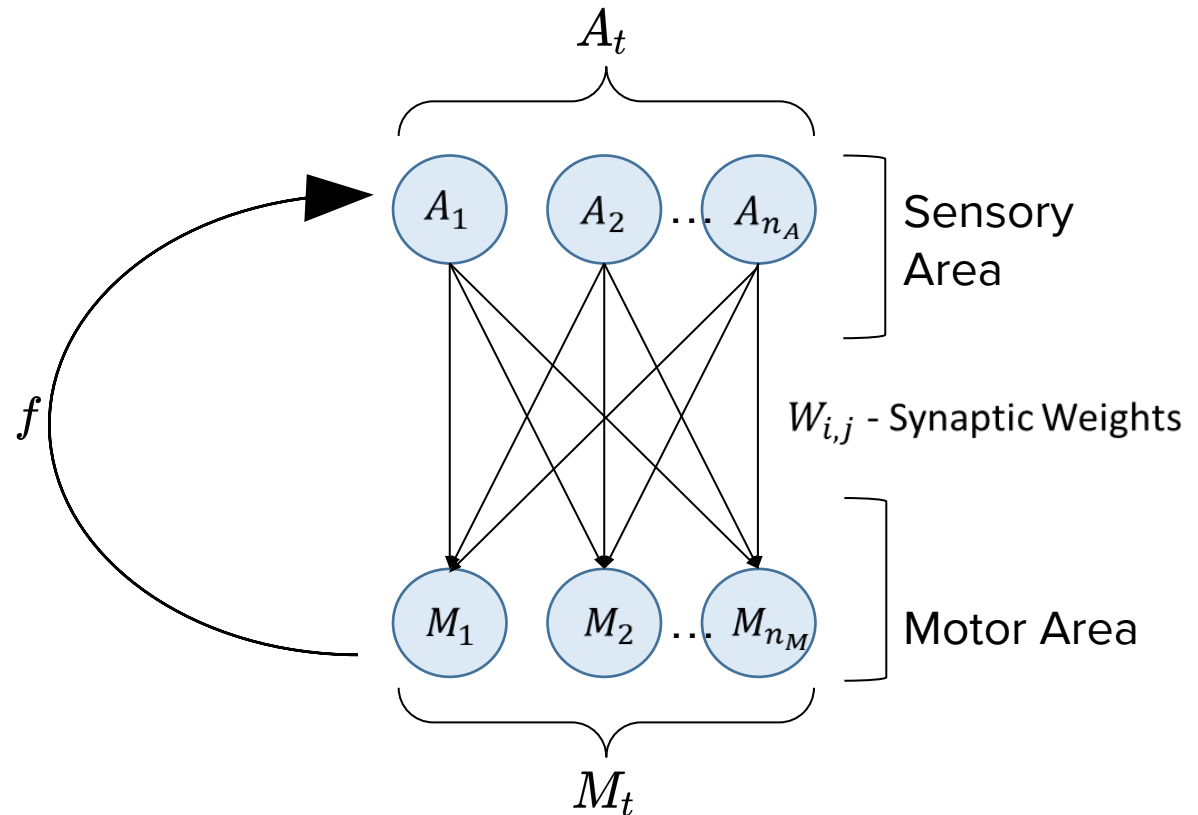


# LEARNING AN INVERSE MODEL

Synaptic weights  $W_{t=t_0}$  initially weak

At each time  $t$  :

- $A_t = f(M_t)$



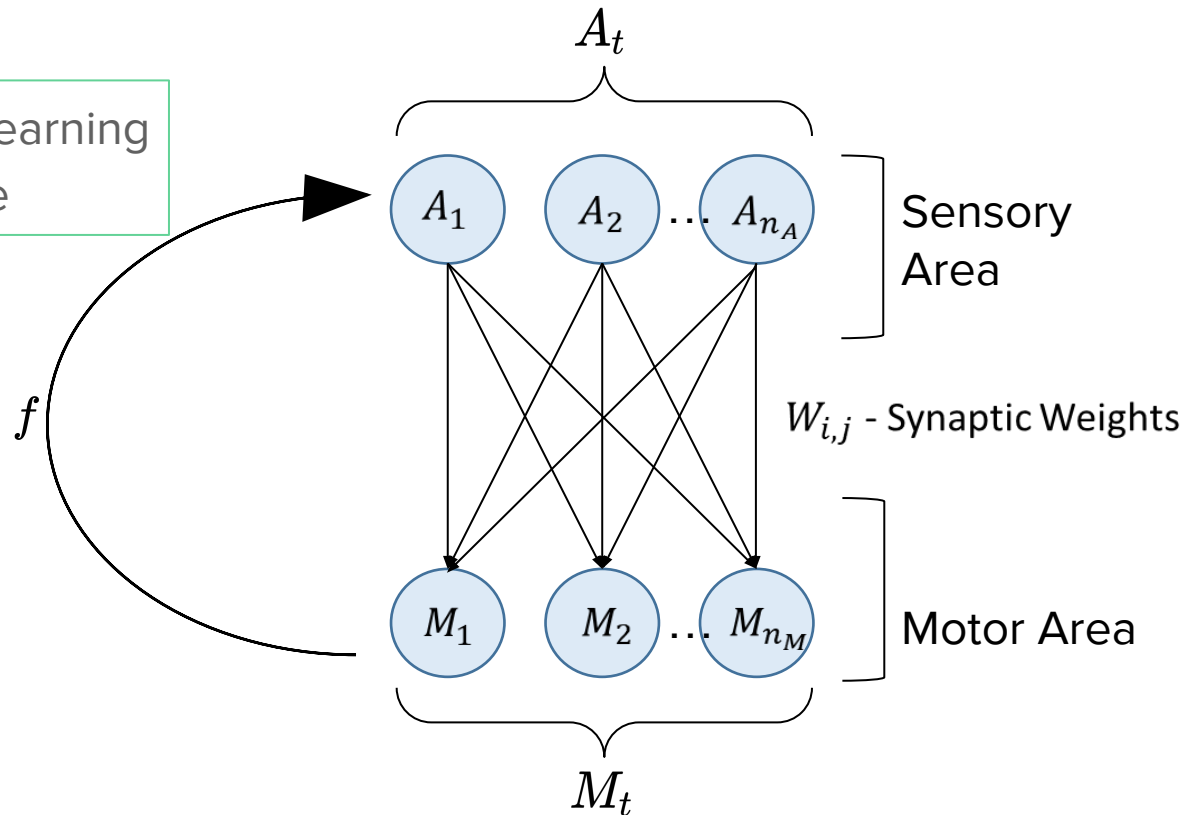
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At each time  $t$  :

- $A_t = f(M_t)$
- $\Delta W_t \propto \eta M_t A_t$

Hebbian learning  
rule



$\eta$  : learning rate

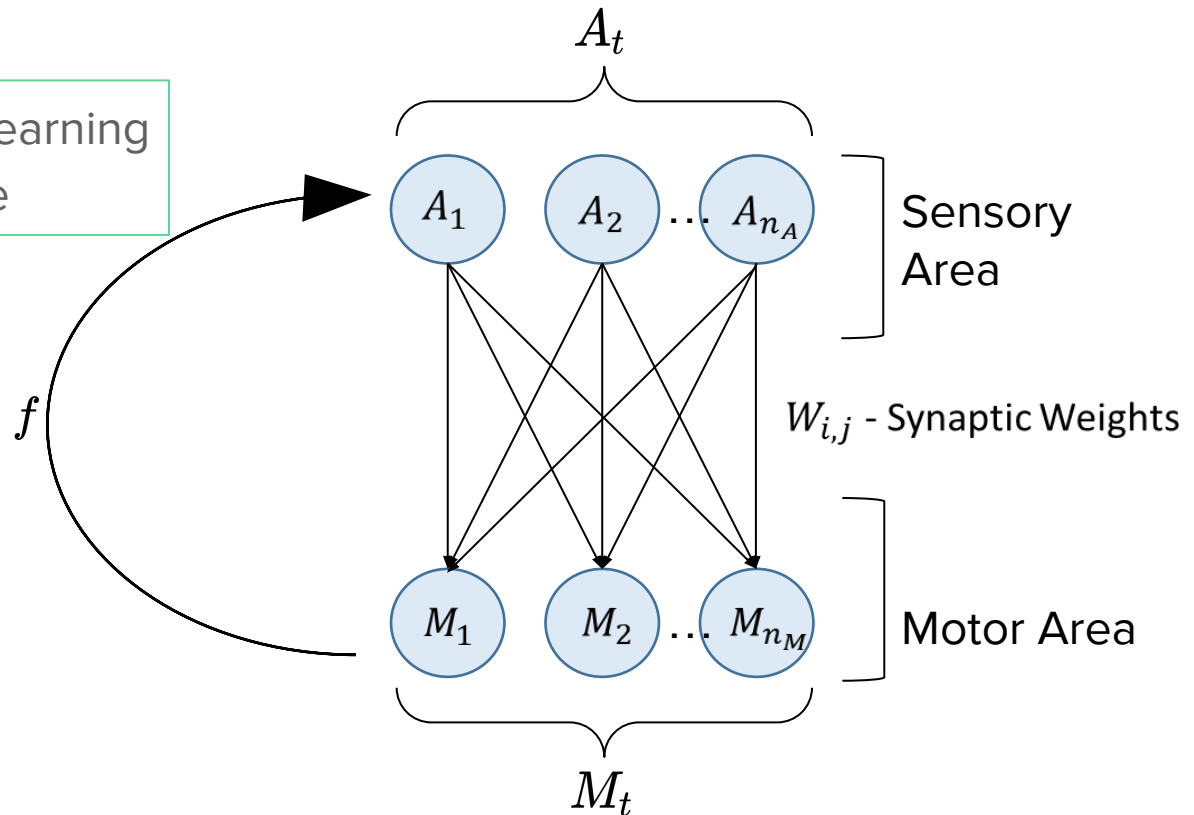
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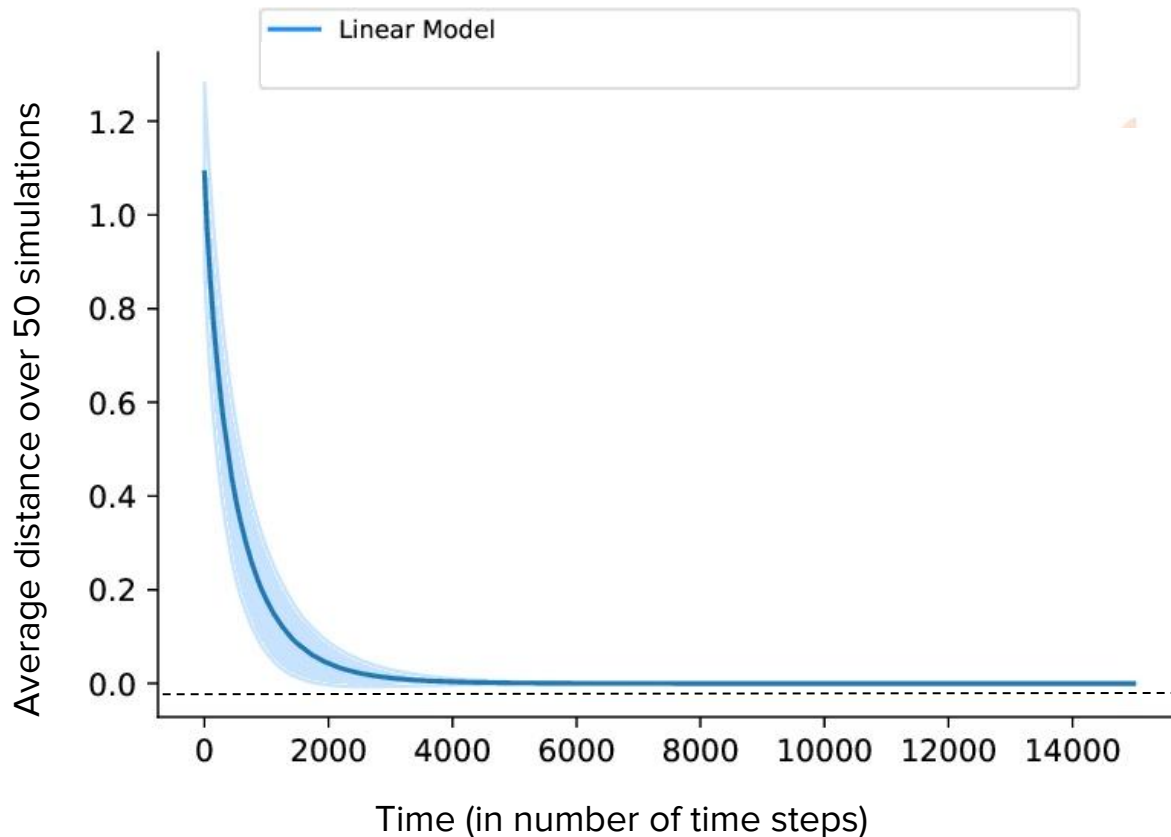
- $A_t = f(M_t)$
- $\Delta W_t \propto \eta M_t A_t$
- $W_t = W_{t-1} + \Delta W_t$

Hebbian learning  
rule



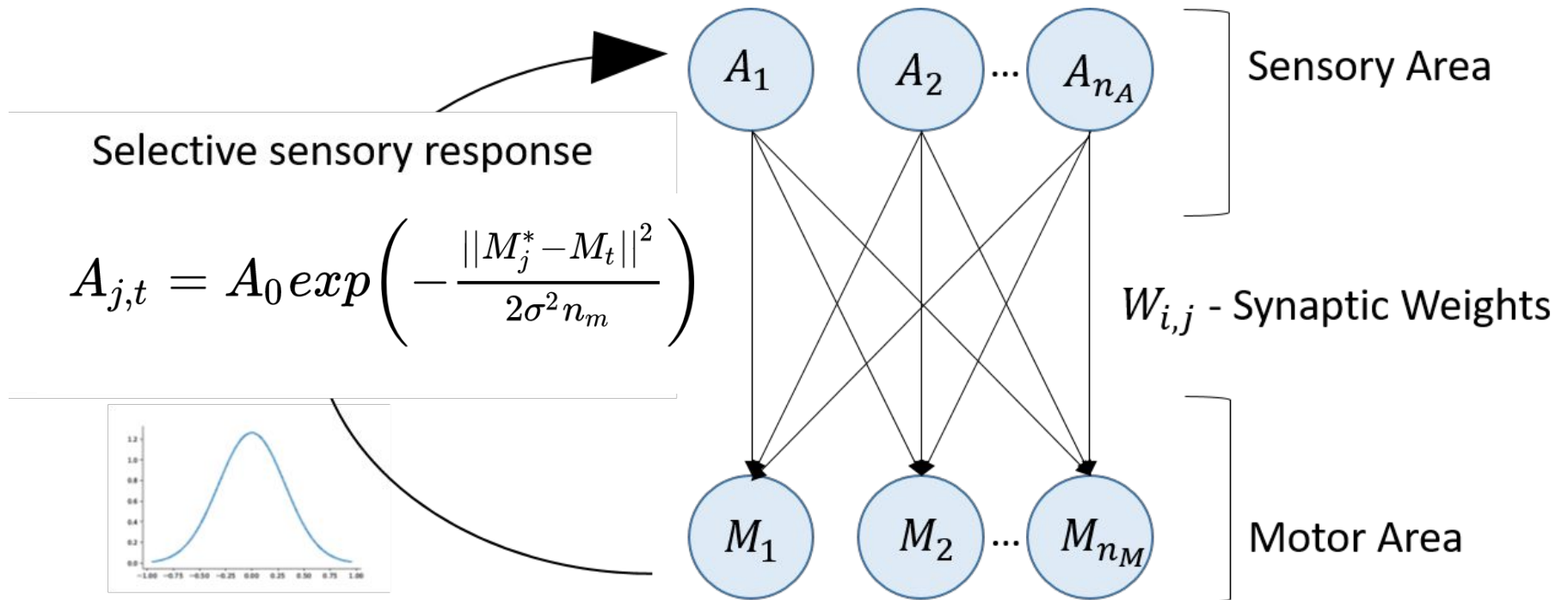
$\eta$  : learning rate

# HAHNLOSER-GANGULI THEORETICAL MODEL



$$\Delta W_t = \eta(M_t - W_{t-1}A_t)A_t^T$$

# NONLINEAR MODEL INTRODUCTION

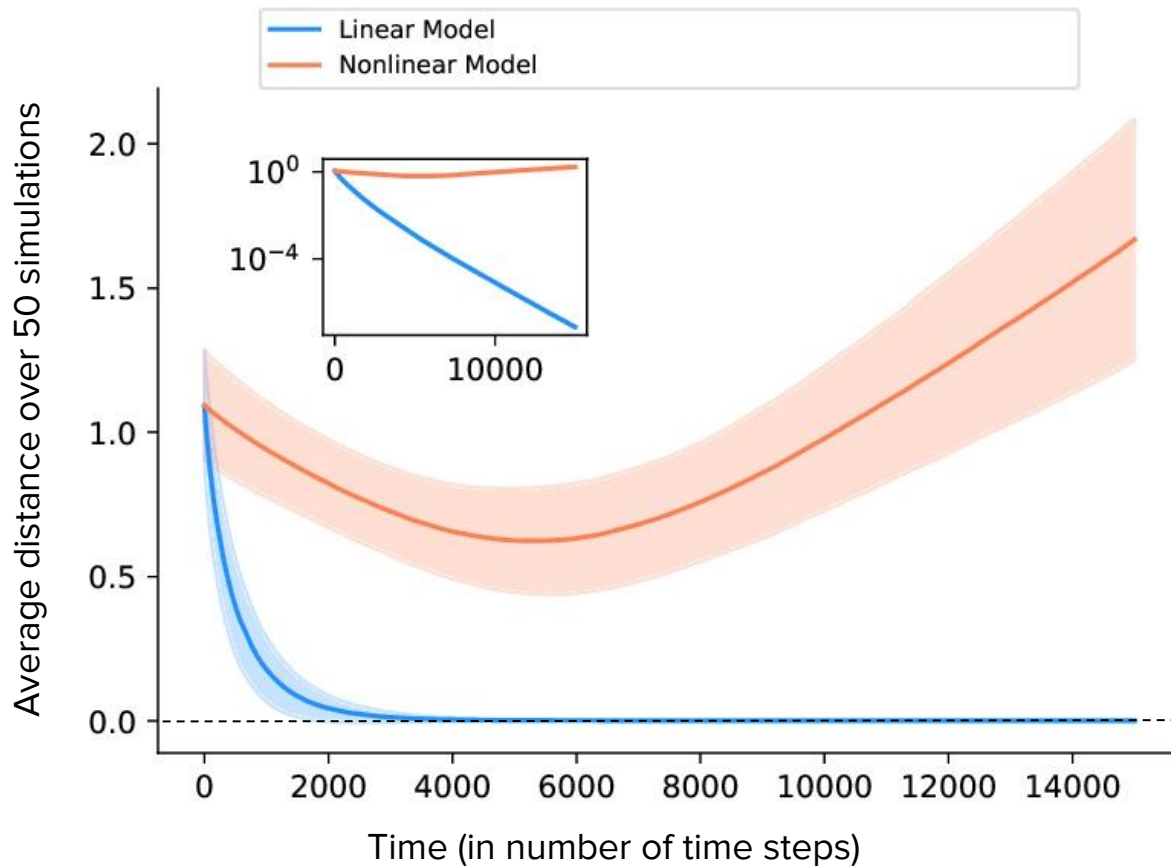


$M^*$  : target motor pattern

$\sigma$  : tuning selectivity width

$||M_j^* - M_t||^2$  represents the distance between the target and the random exploration

# GANGULI-HAHNLOSER MODEL



$$\Delta W_t = \eta(M_t - W_{t-1}A_t)A_t^T$$

# NORMALIZATION

Synaptic weights have a maximal value, related to the number of synaptic receptors one neuron is able to produce.



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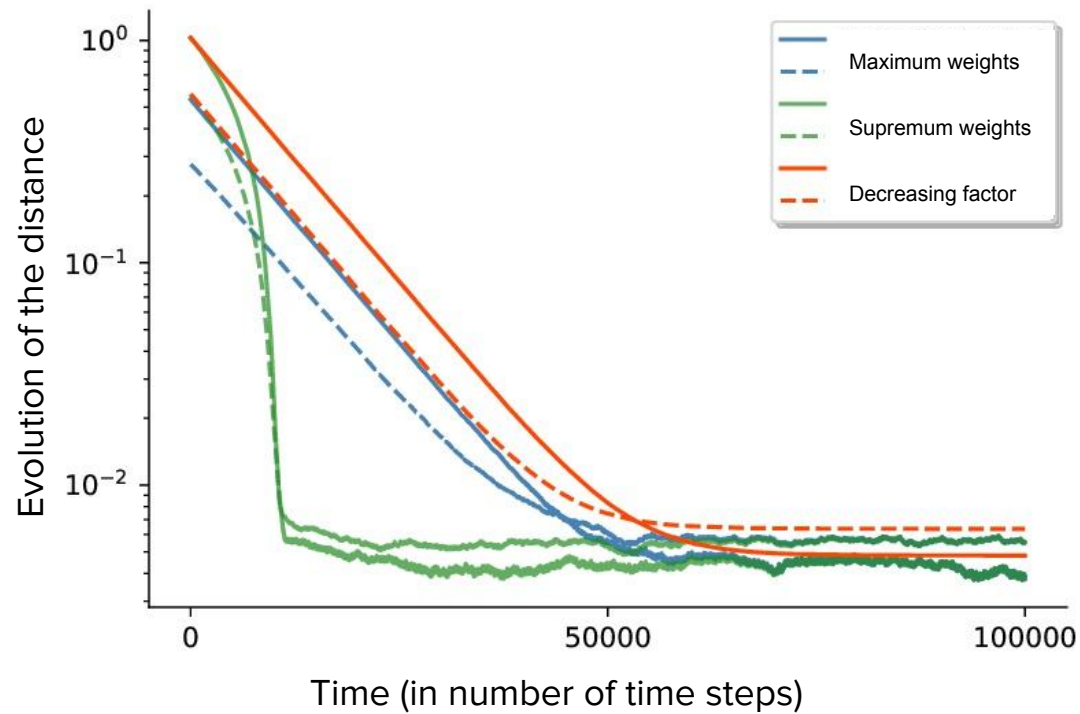
- Maximal weights normalization  $W_{i,j} = \frac{W_{i,j}}{\langle W \rangle_{col}}$
- Supremum weights normalization  $W_{i,j} = \begin{cases} W_{i,j} & \text{if } \langle W \rangle_{col} < 1 \\ \frac{W_{i,j}}{\langle W \rangle_{col}} & \text{otherwise} \end{cases}$

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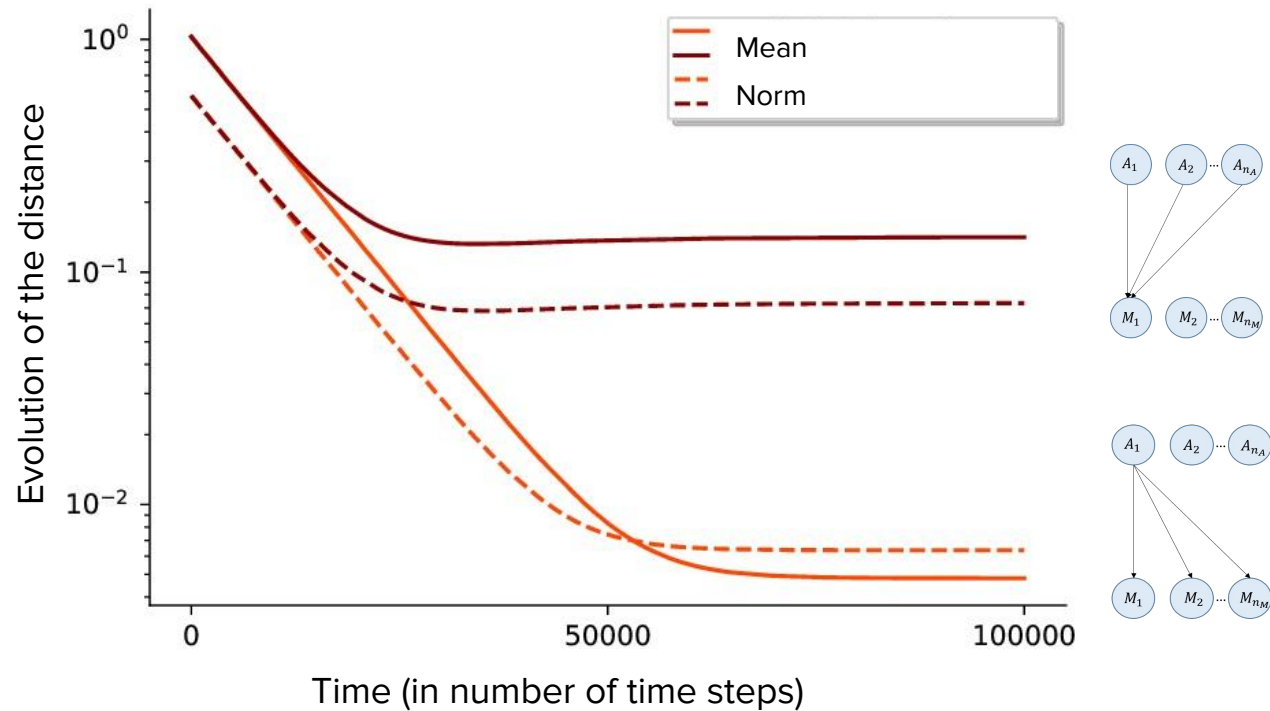
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- Decreasing factor normalization  $\Delta W_{i,j} = \eta M_t A_t \left( 1 - \langle W \rangle_{col} \right)$

# NORMALIZED INVERSE MODEL



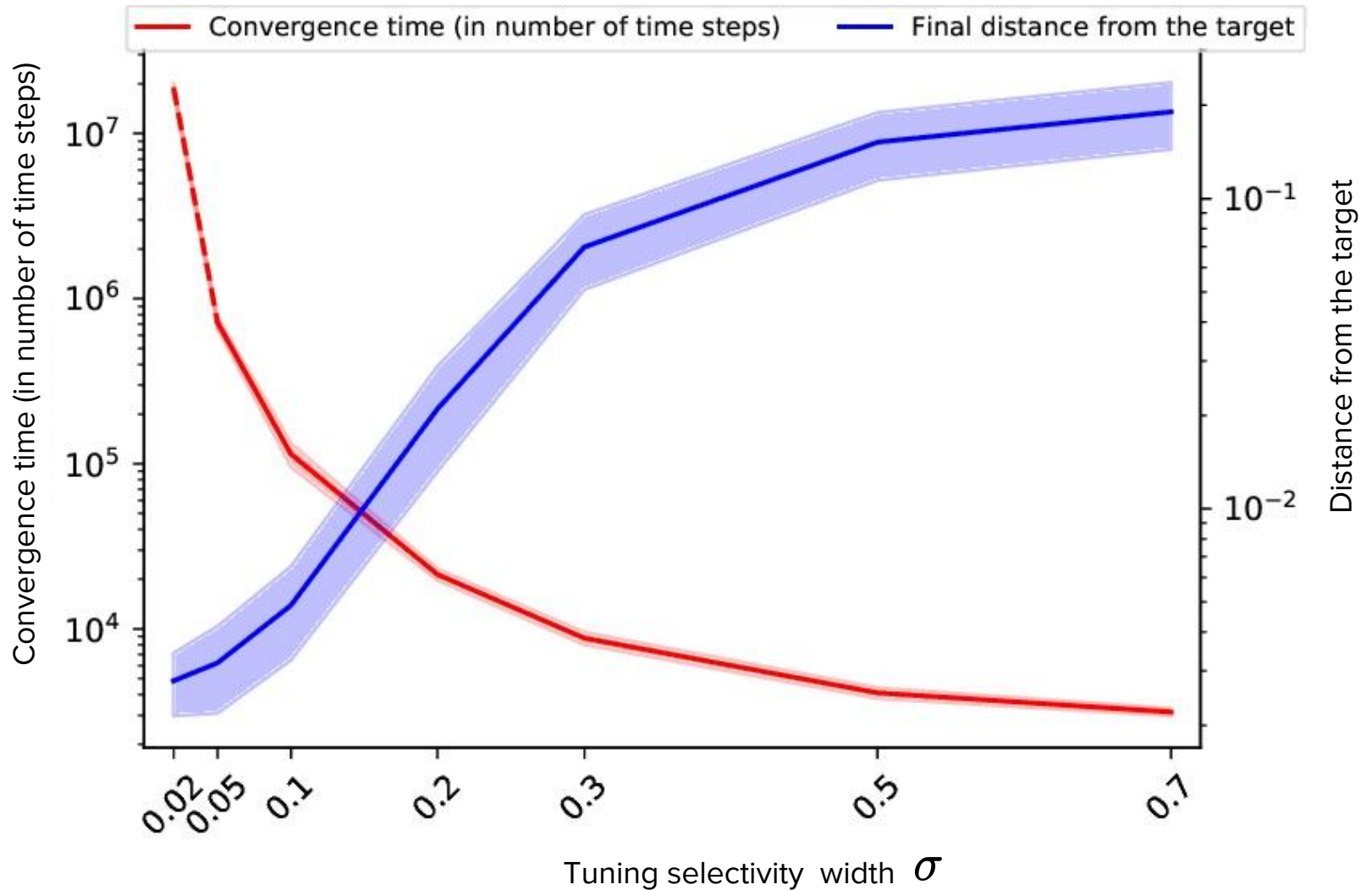
Normalization applied over the auditory neurons

# NORMALIZED INVERSE MODEL

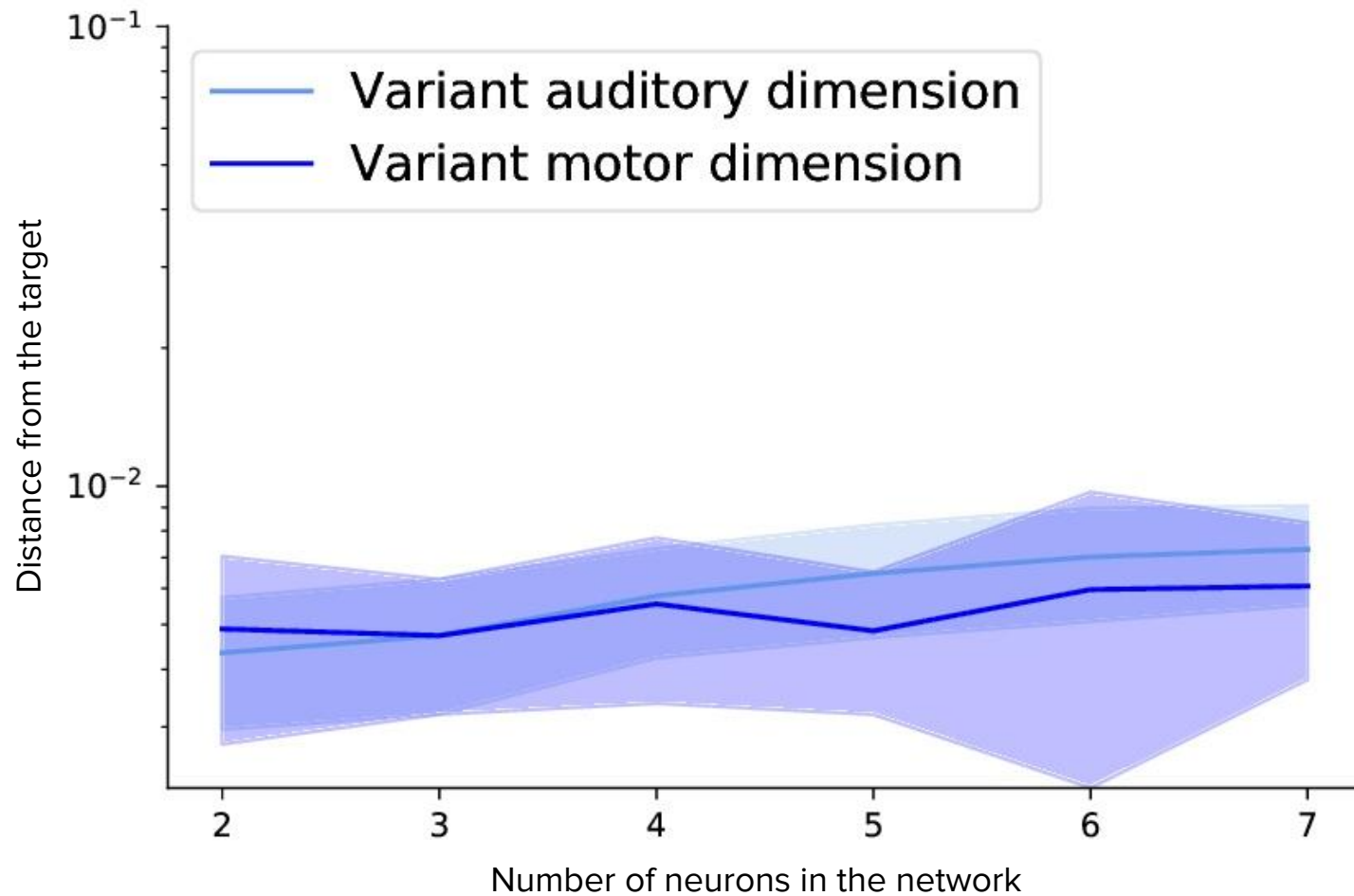


$$\Delta W_{i,j} = \eta M_t A_t \left( 1 - \langle W \rangle_{col} \right)$$

# AUDITORY SELECTIVITY EFFECT

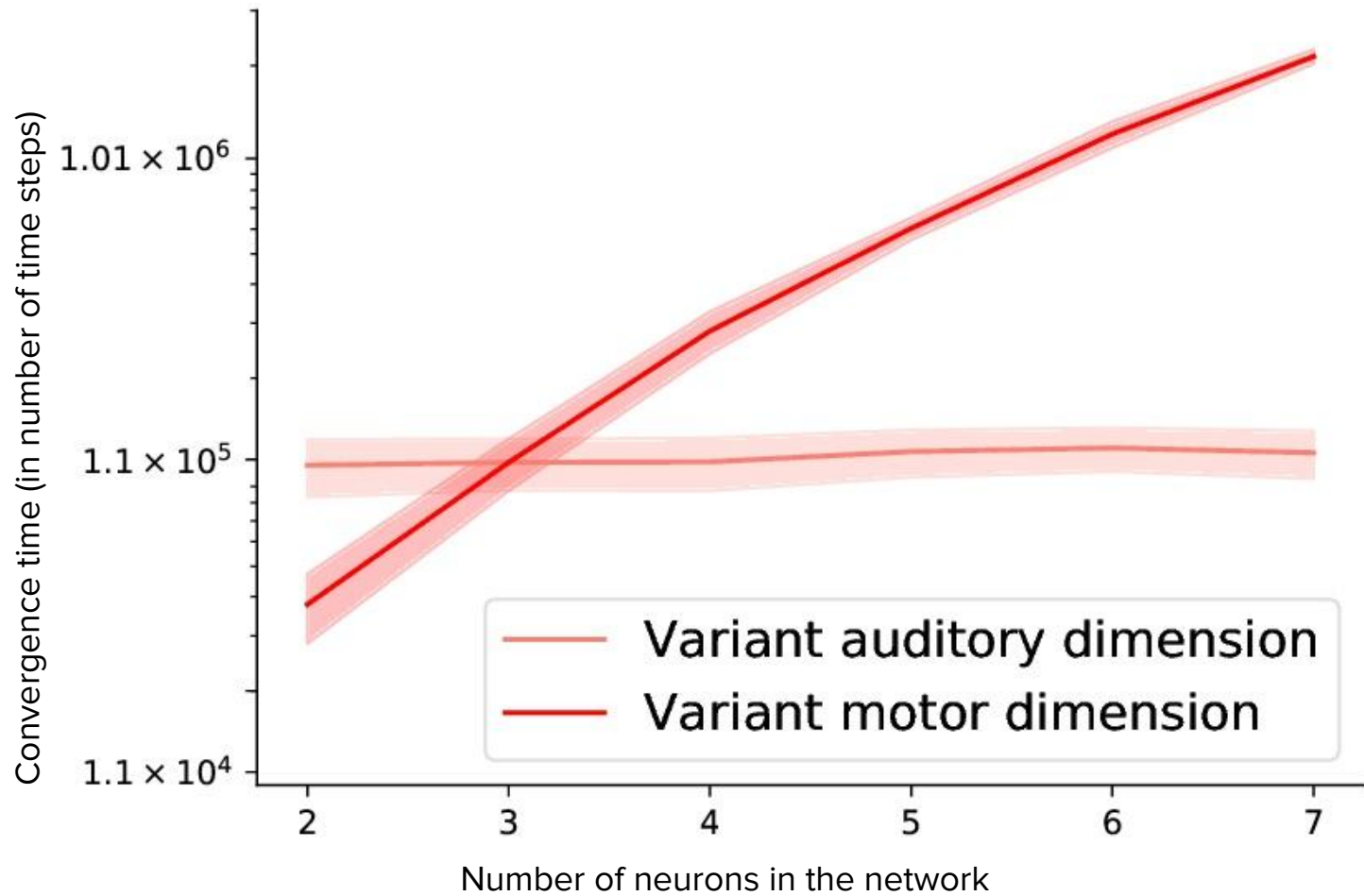


# VARYING INPUT/OUTPUT DIMENSION



Distance from the motor target at convergence

# VARYING INPUT/OUTPUT DIMENSION



Convergence time

# SUMMARY

- Simple normalization schema are successful in the nonlinear model
- Decreasing tuning selectivity width:
  - convergence time explosion
  - accuracy of learning increases
- Auditory VS motor dimension



# WHAT'S NEXT?

- Duration of syllable and feedback delay

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- Production of sound

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- Production of sound

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Xavier Hinaut



# WHAT'S NEXT?

- Duration of syllable and feedback delay
- Production of sound
- Make prediction on experimental data

Enjoy the poster from  
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Thanks for the attention.

$$d_t = \frac{||M^* - W_t A^*||}{n_m}$$